Introduction: Evolution of Brain-Computer Interfaces

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Brain-Computer Interfaces (BCIs) are systems that translate a measure of a user's brain activity into messages or commands for an interactive application. A typical example of a BCI is a system that enables a user to move a ball on a computer screen towards the left or towards the right, by imagining left or right hand movement respectively. The very term BCI was coined in the 70's, and since then, interest and research efforts in BCIs grew tremendously, with possibly hundreds of laboratories around the world studying this topic. This has resulted in a very large number of paradigms, methods, concepts and applications of such technology. This handbook thus aims at providing an overview and tutorials of the multiple and rich facets of BCIs.

As an introduction to this vast endeavor, we would like to present a short and brief history of BCIs, in order to explain where they come from. Figure 1 illustrates BCI technology trends and historical events. Since we are no historians of science, such historical introduction is likely to be incomplete and biased, according to our background, views and (conscious or not) preferences. Nonetheless, we hope this will enable the readers to get a quick overview of the development in BCIs these last 30 or 40 years, and will motivate them to learn more about BCI concepts, which this handbook should make easier.

[INSERT FIGURE 1]

The origins

In the 1920's, a German scientist named Hans Berger was the first to show that the human brain was producing electrical currents. Such currents reflected brain activity and could be measured on the scalp using electrodes: the concept of Electroencephalography (EEG) was born (Berger 1929). EEG proved a key tool in neuroscience, notably to study cognitive functions and their neural correlates, for understanding or diagnosing neuro-pathologies. With the development of EEG, the idea that brain activity could be used as a communication channel or carrier of information also rapidly emerged. Kamiya, in 1968, has notably showed that features of EEG activity - in his studies he considered alpha waves - could purposely be controlled by a human subject after some training (Kamiya 1968). This was the beginning of neurofeedback, a field interested in training users to self-regulate their brain activity thanks to real-time feedback about this activity. This led artists to consider using EEG in their performances. For instance, in the early 1970s, artist Nina Sobell provided participants with a visualization of their synchronized brain activity, to encourage them to get synchronized EEG features

(Sobell 2002) (see also, (Nijholt 2016), for more history on BCI and arts). Then, in 1973, a seminal paper by Jacques J. Vidal, a Belgium researcher working at the University of California in Los Angeles, coined the term “Brain-Computer Interface” (Vidal 1973). In particular, Vidal describe BCIs as “*utilizing the brain signals in a man-computer dialogue*” and “*as a mean of control over external processes such as computers or prosthetic devices*”. Only the concepts were proposed at that time – implementations were ongoing – but the vision and several ideas proposed at that time are still explored and followed today.

While the field stayed kind of dormant in the 70’s and early 80’s, the end of 80’s and beginning of the 90’s saw a handful of researchers from the USA and Europe pioneering the BCI field, by proposing the first real-time and working BCI implementations, which defined several of the major paradigms used today.

The pioneers

In 1988, Farwell and Donchin published another seminal paper, which proposed the now very famous and widely used BCI paradigm known as the “P300-speller” (Farwell & Donchin, 1988). More specifically, they proposed a BCI for spelling letters based on Event-Related Potentials (ERP), which are EEG deflections in response to a specific event or stimulus. In the P300-speller, a 6*6 grid of letters and digits is displayed on a computer screen. The rows and columns of this grid are randomly flashing, and the user is asked to count the number of times the letter he wants to spell is flashed. This way, each time the target letter is flashed, this triggers an ERP known as the P300 in the user’s EEG signals, which can be detected. After several flashes repetitions, it thus become possible to detect which row and which column contains the letter the user wants to spell, and thus to select this letter. Although this system was tested on healthy users only at that time, this showed that BCIs could potentially be used to enable severely paralyzed users to communicate and interact with their environment. In fact, the main driving force behind BCI research at that time, and still a major motivation today, was to use them as a new assistive technology for motor-impaired users, and notably for those that may not have access to any alternative one.

Not long after, both in the USA and in Europe, researchers developed BCIs based on SensoriMotor Rhythms (SMR), i.e., based on the oscillatory EEG activity and notably the mu rhythm (~7-13Hz) over the sensorimotor part of the cortex. In the USA, Jonathan Wolpaw and his colleagues developed a BCI for 1D cursor control based on operant conditioning (Wolpaw et al, 1991). With this approach, users were trained to self-regulate voluntarily the amplitude of their SMR activity in order to move a ball up or down. This was made possible by using neurofeedback, i.e., by displaying to users their SMR activity in real-time, so that they can learn to modulate it. At about the same time in Europe, in Austria, Gert Pfurtscheller and his team were developing another SMR-based BCI, in which users had to explicitly imagine left or right hand movement that were translated into a command for the computer by using machine learning (Pfurtscheller et al, 1993). This defined the so-called motor imagery-based BCIs.

Still in Europe, and during the same period, Niels Birbaumer and his colleagues were working on a third type of BCI paradigm: BCIs based on Slow Cortical Potential (SCP). SCP are low frequency variations of EEG signals amplitude, whose amplitude can be voluntarily increased or decreased using training and neurofeedback. This principle was used to design the “Thought Translation Device” (TTD), which enables a user to select one group of commands or another by respectively increasing or decreasing they SCP amplitude. The TTD was notably used by paralyzed users to spell letters (Birbaumer et al, 1999). The idea was to use the SCP-BCI to select between two groups of letters. The selected letter group was then divided into two sub groups, and the process repeated until only one letter remains in each group, so that they can be selected, enabling the user to communicate by brain activity alone. While SCP-BCI are now really used anymore, due to generally inferior performances, the TTD showed that BCIs were promising tools for severely paralyzed users.

While it did not get as much visibility at that time and even after, Jose Principe and his colleagues also developed an ERP-based BCI at that time in the USA. They developed the so-called “cortical mouse”, which enables a user to select one command among two based on the N400 response to a congruent or incongruent stimulus sentence (Childers et al 1989, Konger et al 1990, Principe 2013).

These pioneering groups essentially defined the BCI field and are all prominent figures in BCI research nowadays. Their work sparked the rapid increase in BCI research that follows the years after.

The bloom of a research field

The end of the last century and the beginning of the new one saw BCI research becoming a research field on its own, with many new research groups joining the efforts, and making the field evolve rapidly. New BCI paradigms were proposed, such as BCIs based on Steady-State Visual Evoked Potentials (SSVEP). SSVEP are oscillatory EEG activity whose frequency is synchronized to that of a flickering visual stimulus, to which the user pays attention. By using several stimuli, each with a specific flickering frequency, the specific SSVEP response to each of them can be associated to a specific BCI commands. Such an SSVEP-BCI was notably used to control the left and right movement of a plane in a flight simulator, using two different flickering lights situated on the left and right of the cockpit (McMillan et al, 1995).

While machine learning was already used for BCIs, more advanced and BCI-specific machine learning tools were proposed by different groups at that time to classify EEG signals in a more robust way, using, e.g., support vector machines or neural classifiers (Anderson et al, 1996, Blankertz et al 2002, Millan et al, 2002). The famous Common Spatial Patterns (CSP) spatial filtering algorithm, which is still kind of a gold standard today, was also proposed back then (Ramoser et al, 2000).

At the same time, research in invasive BCIs on primates was starting. We can notably cite the work of the Nicolelis group, which showed that first rats, then monkeys, could control a robotic arm using neural signals recorded directly from their motor cortex neurons, i.e., with electrodes implanted in their brains (Chapin et al, 1999, Nicolelis 2001).

BCI research groups started at that time to organize themselves as a full research community, with notably the first International BCI meeting which took place in the USA in 1999 (Wolpaw et al, 2000). About 50 participants from 22 research groups participated. At that time, BCIs were defined as "*a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles.*" (Wolpaw et al, 2002)[1].

Modern history

From that time to about now (i.e., 2017), the BCI research field expanded drastically both in size and in scope (Brunner et al, 2015). In terms of size, the 6th (and most recent) International BCI meeting in 2016 gathered about 400 participants, from 188 research groups and organizations (Huggins et al, 2017). The journal "*Brain-Computer Interfaces*" was created in 2013 and published its first issue in 2014 (www.tandfonline.com/loi/tbci20). The international BCI society was also created in 2015, in order to "*to foster research and development leading to technologies that enable people to interact with the world through brain signals*" (bcisociety.org).

Research developments continue to propose many new results, such as new BCI paradigms including new visual or auditory evoked potentials-based BCIs (Gao et al, 2014) or Hybrid BCIs which combine one BCI with another interface or another BCI (Pfurstcheller et al, 2010; Müller-Putz et al, 2015). Invasive BCIs became much more efficient (Lebedev et al, 2006), including now on humans (Hochberg et al, 2006; Collinger et al., 2013). New brain recordings technologies are being explored such as functional Near Infrared Spectroscopy (fNIRS) (Sitaram et al, 2007, Girouard et al, 2010) or ElectroCorticoGraphy (Schalk et al, 2008). On the practical side, consumer-grade EEG sensors and BCI systems are now available on the market (see, e.g., openbci.com), while BCI softwares are available for free and open-source (Brunner et al, 2013). EEG signal processing algorithms improved (Makeig et al, 2012), as well as our understanding of the user side of BCIs, i.e., the user experience, psychology and training (Kübler et al, 2014, Jeunet et al, 2016, Lotte et al, 2013, Neuper et al, 2010).

The scope of BCIs also expanded, and many new BCI applications are now explored, including among others, stroke rehabilitation (Ang et al, 2015), gaming (Nijholt et al, 2009, Lécuyer et al, 2008), many new uses of BCI as assistive technologies (Kübler et al, 2013, Millan et al, 2010), mobile BCI, i.e.,

[1] This paper by Wolpaw and colleagues is a seminal one in BCI research and quite possibly the most cited BCI paper ever. It is a must read for anyone starting with BCIs, as this paper presents most of the concepts, paradigms and challenges of BCI research.

real-time EEG decoding with a moving user (Lotte et al, 2009, Kranczioch et al, 2014), or artistic applications (Andujar et al, 2015), among others. Passive BCIs were also proposed as a new concept of BCI, which are not used for directly sending voluntary commands to an application, but for monitoring the user's' mental states (e.g., attention or workload), to then adapt the target application according to this state (Zander et al, 2011). Sub-categories of passive BCIs notably include affective BCIs, which monitor affective states (e.g., anger or joy) to design applications reacting to these states (Mühl et al, 2014).

This in turn led to increased interest for BCI technologies outside the BCI field, notably in the Human-Computer Interaction (HCI) field, were BCI proved useful for multimodal interaction, intelligent systems or (neuro)ergonomics, among others, see, e.g., (Tan & Nijholt, 2010, Frey et al, 2017). BCI technologies were also shown useful as a new tool for scientific research (Sanchez et al, 2014). To reflect and include such new usages of BCIs, the current definition of BCIs has expanded. A BCI is currently defined as *"a system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment."* (Wolpaw & Wolpaw, 2012).

This book

As this brief historical – but incomplete and partial - chapter showed, the BCI research field is thus now a mature, very rich and highly multidisciplinary research field. As such, starting to work on or with BCIs is a difficult endeavor, which requires learning and mastering multiple disciplines, tools and concepts. In order to make that task easier, and contribute to spreading the use of BCIs and their potential benefits, we have put up together this handbook of BCI, with the help of many renowned scientists from the field. It is our hope that this book would enable any new comer to the BCI field, or even anyone already working on the field but wanting to deepen their BCI knowledge, to find an overview of BCI developments, methods, results and open challenges. We hope this book will provide our readers with the necessary tools and knowledge to conduct new, rigorous and relevant BCI studies as well as to design and build innovative and useful BCI applications and products.

This book is divided into 6 parts, dedicated respectively to BCI applications, brain signals acquisition and software, brain signal processing, BCI paradigms, design and evaluation of BCI experiments and the future of BCI research.

More precisely, part I, dedicated to BCI applications, first starts with an introduction to BCIs (part I.A), with a general overview of BCI systems, how neuroscience and BCIs interact and a presentation of passive BCIs. Then part I.B presents various therapeutic applications of BCI, including using BCI for motor rehabilitation, troubles of consciousness, cognitive rehabilitation, neuroprosthesis or communication, including with elderly users. Part I.C deals with affective and artistic applications of

BCIs, for affect detection, art applications and music. Applications of BCI for entertainment and multimedia are covered in part I.D, with chapters dedicated to BCI-games, BCIs for virtual and augmented realities and BCI for haptics.

Part II gathers chapters dealing with brain signal acquisition, notably invasive ones, and BCI software. Notably, it contains chapters focused on subdermal electrodes (minimally invasive), electrocorticography (semi-invasive) and neurotrophic electrodes (fully invasive). This parts ends with a chapter dedicated to the different softwares that are available to acquire and process in real-time various brain signals such as those above, in order to design a BCI.

Part III is dedicated to the next step in the BCI processing pipeline, namely processing the acquired brain signals. As such, this parts starts with a chapter providing a gentle introduction to EEG signals processing in BCIs, before presenting more advanced material in the subsequent chapters. In particular the next chapters cover EEG signals classification based on Riemannian geometry, more advanced methods for ERP classification and Bayesian learning for BCIs, and transfer learning approaches for BCIs. Many of these methods aim at dealing with the variability of BCI performance over time and users, which is a critical problem in brain signals processing for BCIs.

Part IV explores in more details the various types of BCI paradigms that are available. It indeed gathers chapters dedicated to the most common BCI paradigms that are motor imagery BCIs, P300 and SSVEP BCIs. It also presents more recent and complex BCI designs, namely attention-based BCIs, BCIs with specific stimulus design as well as hybrid BCIs. Two chapters are actually dedicated to hybrid BCIs, with an overview of such paradigms and a specific focus on hybrid BCIs combining SSVEP with eye tracking.

Part V focuses mostly on the last - but no less crucial - element of the brain-computer interaction loop: the user. As such it focuses on human factors, design and evaluation of BCI systems, by considering this key element that the human user is. In particular, this part contains chapters dedicated to usability evaluation in BCI, user-centred design and adaptive BCI design to improve user training and experience. It also provides BCI experimenters and researchers with tools to successfully design and evaluate actual BCI studies on real users. A chapter is indeed dedicated to the design of rigorous BCI experiments, providing guidelines to avoid typical flaws and biases, while another chapter is dedicated to the many ways to evaluate BCI performances, both machine and user ones.

Finally, part VI is dedicated to the future of BCIs and emerging research directions. It notably addresses important ethical issues associated with BCI research and applications, the impact of BCI use on brain plasticity, the emergence of multi-brain BCI systems - that is BCI applications using as input brain signals from multiple users - as well as bidirectional BCIs, i.e., systems that both directly measure from and stimulate the brain. The whole book finishes by a chapter offering perspectives for the whole BCI field.

Now we invite our readers to dive into this book, to learn and get inspired from it, in order to keep the BCI community being a dynamic and innovative community, and to ensure BCI technologies can benefit in practice to those who need them!

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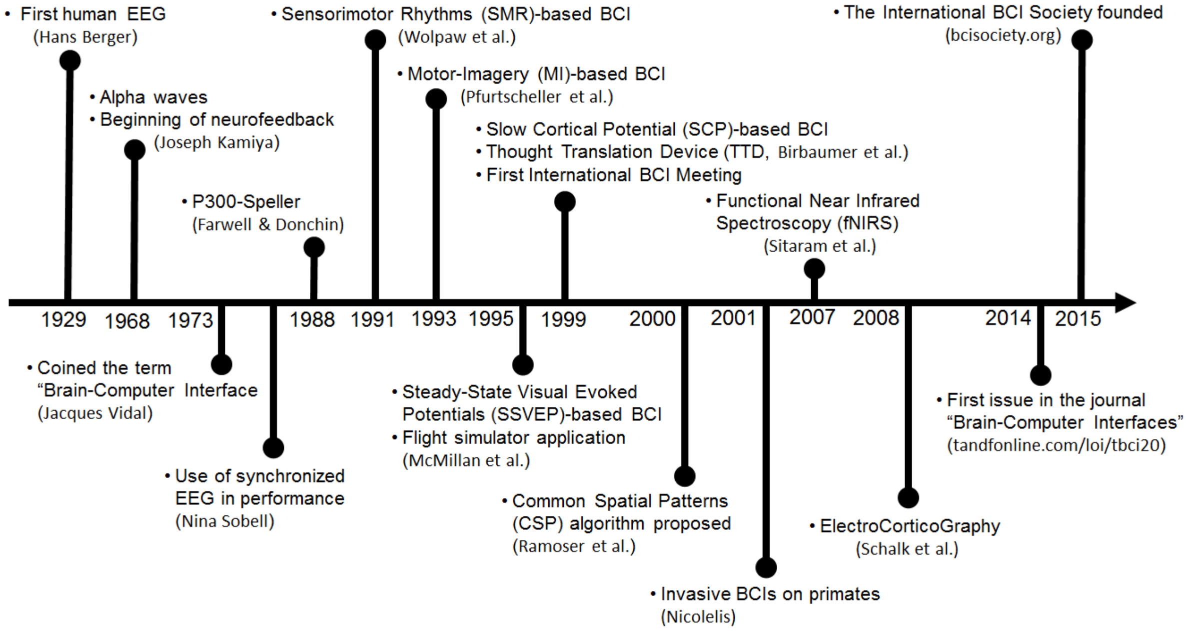
Figure 1. BCI technology and historical events.


• First human EEG
(Hans Berger)
• Alpha waves
• Beginning of neurofeedback
(Joseph Kamiya)
• P300-Speller
(Farwell & Donchin)
• Sensorimotor Rhythms (SMR)-based BCI
(Wolpaw et al.)
• Motor-Imagery (MI)-based BCI
(Pfurtscheller et al.)
• Slow Cortical Potential (SCP)-based BCI
• Thought Translation Device (TTD, Birbaumer et al.)
• First International BCI Meeting
• Functional Near Infrared
Spectroscopy (fNIRS)
(Sitaram et al.)
• The International BCI Society founded
(bcisociety.org)
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• Coined the term
"Brain-Computer Interface
(Jacques Vidal)
• Use of synchronized
EEG in performance
(Nina Sobell)
• Steady-State Visual Evoked
Potentials (SSVEP)-based BCI
• Flight simulator application
(McMillan et al.)
• Common Spatial Patterns
(CSP) algorithm proposed
(Ramoser et al.)
• Invasive BCIs on primates
(Nicolelis)
• ElectroCorticoGraphy
(Schalk et al.)
• First issue in the journal
"Brain-Computer Interfaces"
(tandfonline.com/loi/tbci20)